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The Impact of Expert Knowledge on User Behavior in Recommender Systems

Nils Herm-Stapelberg
Johannes Gutenberg-Universität Mainz, hermstapelberg@uni-mainz.de

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Completed Research

Nils Herm-Stapelberg
Johannes Gutenberg-Universität Mainz
hermstapelberg@uni-mainz.de

Abstract

Using experts in recommender systems can improve the accuracy of recommendations as well as other quality aspects of recommendations. Most studies have tested the impact of expert knowledge in offline tests. However, it is still unclear how user behavior changes when experts are used for recommendation in an online scenario. We therefore deploy a live recommender system based on rules built by employed experts on the video-on-demand platform of a large television network. We find that expert-built rules lead to a similar amount of clip views and platform visits as a standard recommender. However, experts have an influence on the consumed content, focusing users on a few popular categories.

Keywords

Recommender systems, experts, user behavior

Introduction

Recommender Systems are ubiquitous in today's e-commerce and video-on-demand platforms. They filter the massive amount of available products and help users decide which option to prefer (Bobadilla et al. 2011, Wang and Benbasat 2005, Wang and Benbasat 2008). Recommender systems can increase the overall sales volume and make users aware of lesser known products (Hu et al. 2012, Oestreicher-Singer and Sundarajan 2012).

Although many different techniques have been developed to generate recommendations, common systems mainly use similarities between the content of items (content-based filtering) or similarities between users (collaborative filtering) (Bobadilla et al. 2011, Herlocker et al. 2004). Several studies also propose utilizing experts in the process of recommendation (Ahn and Amatriain 2010, Amatriain et al. 2009a, Bao et al. 2012, Lee and Lee 2013, Lee and Lee 2014, Sha et al. 2012). Professional experts have in-depth knowledge of the product catalogue and can recommend even niche products. Amatriain et al. (2009a) argue that experts exhibit a less noisy rating behavior than regular users and can therefore improve the performance of recommender systems. Studies on expert recommenders as well as the field in general have largely focused on improving the accuracy of given predictions, e.g., measuring the difference between predicted rating and actual rating. Since several researches argue that this focus "has hurt recommender systems" recent studies also include other quality indicators, such as the diversity or novelty of recommendation lists (Ge et al. 2016, McNee et al. 2006).

However, there are only few studies which measure the impact expert based systems have on the behavior of users. Especially considering the vendor perspective, the impact on user behavior (e.g. measured in sales or video-on-demand consumption) is an essential factor on evaluating the benefits of a recommender system. Besides overall sales, it is also of interest to platform providers to understand the influence on content consumption. Video-on-demand platforms such as Netflix might want to promote their own produced series and movies rather than licensed items. E-Commerce platforms such as Amazon might be interested in promoting items of their long tail or products with a high sales margin. Public institutions can have the mission to promote educational and cultural content. It is therefore important to know the impact of recommender systems on content consumption.

Thus, this paper examines the performance of recommendations based on expert-built rules. We deploy a live recommender at a popular video-on-demand website that features a wide variety of content and recruit participants from the regular website visitors. The goal of this paper is to understand the impact expert recommendations have on user behavior. More precisely, it studies the number and category of the watched clips as well as the number of platform visits. We find that expert-built rules perform similarly to a standard recommender concerning clip views and visits. However, there are significant differences regarding the distribution of consumed content. Users who received expert-built rules watched significantly more movies, and significantly less nature documentaries, tourism and travel clips as well as economics related content. Expert-built rules lead to a focus on few top categories rather than diversifying user behavior.

Related Work

Expert recommenders utilize the specific knowledge of domain experts to improve the quality of recommendations and reduce several drawbacks of standard recommenders. As Lee and Lee (2014) state, "the key of this concept is that expertise, or knowledge, should be transferred from experts to novices". There are different types of experts. Many previous studies identify experts from the set of regular users based on e.g. the amount of likes from other users (Sha et al. 2012), location (Bao et al. 2012, Lu and Caverlee 2015) or activity (Cho et al. 2007). Others used publicly available data from actual experts on rating portals such as Rotten Tomatoes (Amatriain et al. 2009a, Yun et al. 2011). Experts have also been used in other areas to improve the quality of decision or recommendation tasks such as the composition of stock portfolios (Hill and Ready-Campbell 2011). Using professional as well as user experts in the context of recommender systems yields many advantages.

Accuracy

The accuracy of recommendations is often assessed by measuring prediction accuracy, i.e. the difference between predicted rating and actual rating of items (e.g., root mean squared error), or classification accuracy, e.g. the share of correctly recommended items that were actually useful for a user compared to all recommended items (Precision). Multiple studies show that the accuracy of recommendations can be increased when using the knowledge and experience of domain experts. Yun et al. (2011) use a combination of user data and expert opinions to reduce the sparsity of the user-item rating matrix and use a variation of singular value decomposition for recommendation. They are able to improve prediction accuracy by adding knowledge of professional experts from the website Rotten Tomatoes to collaborative filtering. Other studies promote experts from the general user population to improve the accuracy of their recommender system. Bao et al. (2012) for example use location information of users to identify "local experts" which are used to recommend sightseeing places to visitors. These local experts have rated many different items in a certain geographical area and are therefore assumed to have in-depth knowledge of high quality attractions. Using a collaborative filtering approach, users are only compared to these experts instead of every user. These studies cover most of the common accuracy indicators. More precisely, using experts is associated with an increase in classification accuracy (e.g., Precision, Recall) as well as prediction accuracy (e.g., root mean squared error).

Diversity

Many studies have shown that recommender systems are not useful for users, when they solely focus on the accuracy of predictions. Instead, it is important to suggest diverse items (Ge et al. 2016, McNee et al. 2006). Measures of diversity include the average pairwise distance of items in a recommendation list (Ziegler et al. 2005) based e.g. on the category of content and other metadata or the number of recommended niche items (Liu et al. 2011). A study by Liu et al. (2011) shows a significant diversity improvement when experts are used for preference elicitation of new users compared to several standard recommenders.

Novelty / Serendipity

Novelty and serendipity are sometimes used synonymously and describe the extent to which items are previously unknown to users. Based on the definition by Kotkov et al. (2016), serendipity additionally captures how unexpected a recommendation is to users. Obvious recommendations might be accurate as well as novel but not useful as users would have discovered the content on their own, without the help of a recommender. Since the feeling of surprise or unexpectedness is subjective, serendipity and novelty are often measured through questionnaires (Kotkov et al. 2016). Due to the specific knowledge of experts, they are able to recommend niche, lesser-known products and therefore increase novelty as well as serendipity (Lee and Lee 2013, 2014).

Missing Data and Cold Start

Recommender Systems are often not able to generate meaningful recommendations for new users that have rated only few or no items. In addition, collaborative filtering systems are not able to recommend new items, that haven't been noticed by many users yet. Experts typically have rated many different items, are motivated to explore and rate new ones, have knowledge of a lot of the available catalogue and are therefore able to recommend even lesser-known items for niche interests with fewer ratings (Amatriain et al. 2009a, Lin et al. 2012, Liu et al. 2011). They can therefore reduce the problems of cold start scenarios.

Natural and Malicious Noise

Users can intentionally or unintentionally introduce noise in their ratings. Malicious attacks on a recommender, e.g. to make one's own product appear at the top of a recommendation list, can reduce the overall quality of the system (O'Mahony and Hurley 2006, Williams et al. 2007). Natural noise can occur due to different reasons. Amatriain et al. (2009a, 2009b) describe that users are inconsistent when rating the same movie at two different points of time. Additionally, users can interpret a certain rating differently based on their personal rating behavior (e.g. benevolent users who often award the maximum possible rating, critical users who only award the maximum rating for the best item they ever consumed). Different approaches have been developed to normalize ratings in order to make them comparable (Amatriain et al. 2009b, O'Mahony and Hurley 2006, Yera et al. 2015, Year et al. 2016). Domain experts with a lot of knowledge of a specific subject can compare items better and are expected to be more consistent with their ratings, introducing less noise (Amatriain et al. 2009a, 2009b, 2009c).

Privacy

Amatriain et al. (2009a) and Ahn and Amatriain (2010) argue that expert driven systems can help reduce the necessary data that is transmitted and used for calculation of recommendations. Collaborative filtering systems could, e.g., only use a comparison of several expert profiles to a user profile instead of comparing every user. Therefore, personal data of a normal user would not be regularly used for recommendation of items to other users, improving the privacy aspect of the system.

Trust

The amount of trust users have in the system (e.g., that it can generate useful recommendations) can influence the perceived quality of that system. Users often trust individuals with a high level of domain expertise more than the general user population (Smith et al. 2005). It can therefore be expected that using experts for recommendation increases satisfaction and use of a system as long as users are aware that experts made the suggestions.

Study Design

Data was collected from the online video-on-demand service of a large television network that offers a wide variety of content (e.g., movies, sports, news, and documentaries). Currently, more than one million users visit the platform each month and more than 100,000 different video clips are available. Recommender systems can help users handle the vast amount of content provided by the service. To evaluate the impact of expert recommendations, we deployed an available commercial recommender and compared it with expert-built rules. These experts are professionals, employed by the television network. They are responsible for the online content provided and regularly curate sets of clip suggestions. Thus, they are able to identify relations between content and built suitable recommendation rules.

Recommender Setup

Users who opted to participate in the study were randomly assigned to one of two groups. Both groups received recommendations on each individual clip website (beneath the currently watched clip). The control group received suggestions generated by the commercial recommender.

The recommendations of the commercial recommender are based on a Naive Bayes classifier. It utilizes information on a certain clip to decide which class the item belongs to (e.g. recommend item, do not recommend item). It is based on the overall likelihood of the classes, the likelihood a given feature of an item belongs to one of the classes, and the likelihood of the features. The probability an item belongs to either of these classes C_i given n features $f_1,\dots f_n$ is described as (Lika et al. 2014, Zhang & Iyengar 2002):

$$p(C_i|f_1,\dots,f_n) = \frac{p(C_i)\prod_{j=1}^{n} p(f_j|C_i)}{p(f_1,\dots,f_n)}$$

$p(C_i)$ describes the probability of class C_i in the whole dataset, $p(C_i|f_1,\dots,f_n)$ denotes the probability of class C_i given the features $f_1\dots,f_n$, $p(f_j|C_i)$ is the probability of feature f_j given class C_i and $p(f_1,\dots,f_n)$ describes the likelihood of the given features of an item.

Users of the treatment group received recommendations based on expert-built rules instead. A team of multiple employed experts built rules based on their knowledge and previous experiences. This resulted in a total of 84 different expert-built rules which were implemented for recommendation. Examples of the rules can be found in Table 1.

Rule Description
If the user is watching a movie, the recommendations should contain at least 3 other clips aligned with the main content of the movie.
If the user is watching a movie, recommend recent clips from the categories Crime Thriller and Documentary on position 4 or later of the recommendation list.
If the user is watching a series, recommend the 2 most recent clips of that same series.
If the user is watching content for children, only recommend more clips suitable for children.
If the user is watching news, do not recommend clips older than 7 days.
If the user is watching news, do not recommend fictional content.
If the user is watching politics related clips, recommend content that contains the main politicians / persons of that clip.

Table 1. Examples of expert rules.

Data Collection

Users who regularly visited the video-on-demand platform received a pop-up, shortly explaining the purpose of this study and asking them to participate. A total of 1,260 users opted to voluntarily be part of the study. We did not provide any incentive for participation and users were only asked for a valid e-mail address and a password to sign up. They were able to provide additional optional information such as their age, gender and location.

Users were not aware of the exact circumstances of the study to avoid biases in user behavior. More precisely, they had no knowledge of the used recommendation techniques. Aside from the generated recommendations, the provided content, the functionality as well as the design of the video-on-demand platform were identical across study groups and the regular platform participants were used to.

Introducing new features often leads to “discovery” effects (Rabbi et al. 2015, Rodriguez et al. 2012). We therefore do not consider the data of the first week of the study. This also allows gathering some preliminary data on users’ preferences to use for recommendation. We can therefore assume that cold start issues, i.e., the lack of enough information on users’ preferences or item consumption do not affect our study (Lika et al. 2014).

We observed user behavior by recording clickstreams that contained every user’s interaction with the video-on-demand platform. 453,066 interactions were recorded over a timeframe of 68 days which feature a total of 55,743 clip views. Metadata on the clips (e.g., its content category such as documentary) were provided by the television network.

Results

To assess the impact of recommendations based on expert-built rules, we compared the two groups across different user behavior indicators. These measures include (see, e.g., Knijnenburg et al. 2012):

- Total number of watched clips (Viewed Clips)
- Total number of platform visits (Total Visits)
- Number of visits where at least one clip was watched (Active Visits)
- Number of visits where multiple clips were watched (Multiclip Visits)
- Number of days a user returned to the platform during the study compared to the length of the study (Return Rate)

Measure	**Control Group (System)**	**Treatment Group (Experts)**	**Absolute Difference**	**Relative Difference**	**Significance**
Viewed Clips	43.11	44.20	+ 1.09	+ 2.53%	> 0.1
Total Visits	31.17	31.96	+ 0.79	+ 2.53%	> 0.1
Active Visits	21.88	23.44	+ 1.56	+ 7.13%	> 0.1
Multiclip Visits	6.71	7.01	+ 0.30	+ 4.47%	> 0.1
Return Rate	0.2643	0.2693	+ 0.005	+ 1.89%	> 0.1

Table 2. User behavior results

The results of these measures can be found in Table 2. Even though there are tendencies that users that received expert-built rules showed more activity, none of these differences is statistically significant. Users of the treatment group (expert-built rules) viewed on average 44.20 clips compared to 43.11 in the control group (+2.55%). They visited the platform 31.96 times (vs. 31.17, +2.53%). Active visits (23.44 vs. 21.88, +7.13%) as well as multiclip visits (7.01 vs. 6.71, +4.47%) show a similar trend, though again, not significant.

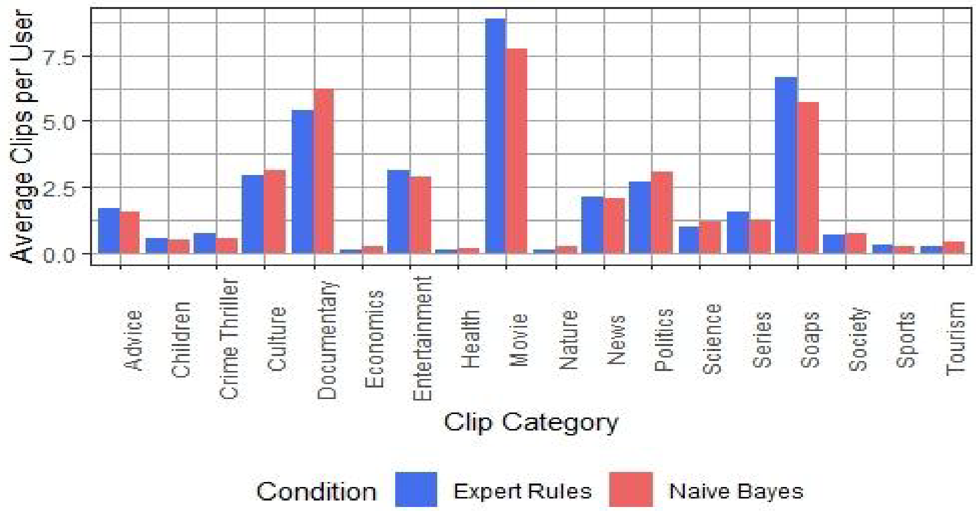

Figure 1. Consumed content distribution

Content Category	Control Group (System)	Treatment Group (Experts)	Absolute Difference	Relative Difference	Signifi-cance
Advice	1.59	1.66	+ 0.07	+ 4.4%	> 0.1
Children	0.50	0.54	+ 0.04	+ 8.0%	> 0.1
Crime Thriller	1.14	1.52	+ 0.38	+ 33.3%	> 0.1
Culture	3.13	2.96	- 0.17	- 5.4%	> 0.1
Documentary	6.21	5.40	- 0.81	- 13.0%	> 0.1
Economics	**0.25**	**0.12**	**- 0.13**	**- 52.0%**	**0.026****
Entertainment	2.85	3.13	+ 0.28	+ 9.8%	> 0.1
Health	**0.16**	**0.07**	**- 0.09**	**- 56.3%**	**0.057***
Movie	**7.76**	**8.88**	**+ 1.12**	**+ 14.4%**	**0.019****
Nature	**0.26**	**0.11**	**- 0.15**	**- 57.7%**	**0.054***
News	4.10	4.18	+ 0.08	+ 2.0%	> 0.1
Politics	3.08	2.70	- 0.38	- 12.3%	> 0.1
Science	1.19	0.97	- 0.22	- 18.5%	> 0.1
Series	1.22	1.58	+ 0.36	+ 29.5%	> 0.1
Soaps	5.69	6.66	+ 0.97	+ 17.0%	> 0.1
Society	0.74	0.68	- 0.06	- 8.1%	> 0.1
Sports	0.25	0.32	+ 0.07	+ 28.0%	> 0.1
Tourism	**0.44**	**0.26**	**- 0.18**	**- 40.9%**	**0.045 ****

Table 3. Content distribution differences. Significance cutoffs are p < 0.1*, 0.05 **, 0.01*. Significance values are calculated by using Mann-Whitney-U tests.**

Since even small increases in these measures can lead to a notable practical impact, it is necessary to repeat the study with a larger user base over a longer timeframe. Advertisement based revenue is directly affected by the amount of clip views on video-on-demand platforms such as Youtube. It would therefore be highly beneficial for platform providers if they could achieve an increase in clip views by 2.55% as in this study.

We further examine whether expert-built rules have an impact on the consumed content. The platform features a total of 18 different content categories. Thus, we compare each content category between the conditions. A comparison of the average clips a user watched in each category can be found in Figure 1 and Table 3.

Users who received expert-built rules watched significantly more movies (+ 14.4%) and significantly less economics (- 52%), tourism (- 40.9%) and health (- 56.3%) related content as well as nature documentaries (- 57.7%). Since movies is the most watched category on the platform and the other 4 are niche categories (less than 1 view on average per user), it indicates that expert-built rules concentrate viewership on few popular categories rather than diversifying viewing behavior.

This becomes especially apparent when clustering the categories based on their popularity, i.e., on the number of watched clips per user in each category. "Top 3" categories have more than 5 clip views per user on average across conditions (movies, soaps and documentaries), "bottom" categories less than 1 clip view per category containing the categories children, economics, health, nature, society, sports and tourism. Categories that were watched between 1 to 5 clips per user are classified as "mid" (advice, crime thriller, culture, entertainment, news, politics, science and series). The results can be found in Table 4. Users who received recommendations based on expert-built rules watched less clips of the "bottom" popularity cluster (- 18.2%). They watched significantly more clips of the top 3 cluster (+ 6.5%) though.

Content popularity cluster	**Control Group (System)**	**Treatment Group (Experts)**	**Absolute Difference**	**Relative Difference**	**Significance**
Bottom (less than on view per category on average)	2.58	2.11	- 0.47	- 18.2%	> 0.1
Mid (1-5 views)	18.30	18.71	+ 0.41	+ 2.2%	> 0.1
Top 3 **(> 5 views)**	**19.66**	**20.94**	**+ 1.28**	**+ 6.5%**	**0.061 ***
Top 2 **(> 6 views)**	**13.45**	**15.54**	**+ 2.09**	**+ 15.5%**	**0.006 *****

Table 4. Content cluster differences. Significance cutoffs are p < 0.1*, 0.05, 0.01*****

Considering only the top 2 categories, the difference is even greater (+ 15.5%). Experts therefore promote already popular categories to increase their consumption. Depending on the use case, this can be both positive and negative. HBO could further promote already existing blockbusters such as Game of Thrones, while Amazon could be more interested in focusing on their long tail of products. Additionally, previous research suggests that user satisfaction and the overall quality of recommender systems can improve when the diversity of given recommendations increases. It is therefore possible that expert-built rules have a negative influence on customer satisfaction since they focus users on few popular categories and do not lead to a diverse consumption of content. Additionally, the effect of focusing users on few popular categories is interpreted differently based on the domain the platform is situated in. Public service broadcasters' (PSBs) mission is to broadly and diversely inform the public of societal issues and current topics (Helberger 2019). Reducing the diversity of consumed content could therefore be detrimental to their public-service remit. This is especially interesting in this context since the European Broadcasting Union (EBU) actively encourages PSBs to use editorial curation in their online services (EBU 2017).

We can therefore assume that expert-built rules have an influence on the content distribution of consumed clips. More precisely, expert-built rules concentrate viewership on a few popular categories rather than diversifying viewing behavior to the benefit of niche categories.

Conclusion

In this paper, we examined the impact of recommendations based on expert-built rules on user behavior. By deploying a live recommender on a popular video-on-demand platform, we were able to show that expert-built rules perform similar to a standard recommender system in terms of clip views, visits, active visits and multiclip visits. Even though all measures show a tendency that expert-built rules positively influence user behavior, no differences were significant. However, we were able to show that expert-built rules influence the distribution of content consumed by the users. Participants who received expert-built rules were more likely to watch movies and less likely to watch economic, health or tourism related content as well as nature documentaries. Expert-built rules therefore focused viewership on popular categories rather than diversifying consumption.

There are several limitations. First, we tested expert-built rules instead of experts recommending specific clips. The expert knowledge used is therefore limited to more general information on which categories fit together rather than the quality of individual clips. This would require significant effort by the experts since the available catalogue of the video-on-demand platform changes daily and features more than 100,000 clips. It is also difficult for experts to make personalized suggestions when the user base is very large.

Second, we tested one standard recommender against expert-built rules. There is a wide variety of different recommendation techniques available that can influence user behavior as well as the consumed content distribution. Multiple studies have shown that combining different techniques can lead to more accurate recommendations and there are systems available that directly focus on other quality indicators such as diversity.

It is unclear whether these findings hold for other video-on-demand platforms. The offered content can differ as well as characteristics of the platform users. It is therefore necessary to repeat the study on multiple video-on-demand platforms.

Additionally, it is important to explore possible influencing factors of the results. So far, the causal relationship between different expert recommendations and their outcome is unclear. It is possible, that recommendations made by experts are, e.g., less or more diverse, accurate or serendipitous than system-generated suggestions. Previous research, e.g., suggests that diverse recommendations can increase user satisfaction by easing the burden of choosing a suitable product for consumption. It is therefore necessary to analyze the given recommendations of experts regarding their impact on different recommender system quality indicators such as the diversity, serendipity or coverage of given suggestions.

Another interesting research area is to explore the collaboration between systems and experts. In our study, expert knowledge was not combined with the wisdom of the crowd (e.g., through collaborative filtering). Experts however might have knowledge and experiences that allow them to improve the recommendations of state-of-the-art systems.

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